Markov Chain Modelling-Based Approach to Reserve Electric Vehicles in Parking Lots for Distribution System Energy Management

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***Abstract*—Integration of renewable energy resources in distribution networks with intermittent behaviour increases the challenge of power balance in transmission systems. To mitigate the undesired impacts, transmission operator involves distribution operators to get local contribution from their flexible resources. In this paper, we address the flexibility offered by some electric car sharing agents which can serve some reserve capacity to distribution system. A Markov Chain modelling based approach is proposed to support system operator to properly estimate the number of electric vehicles required to be booked in advance as reserve. Underestimation would result in imperfect demand correction, and overestimation would imply extra costs. Using a realistic case under a near future scenario of high PV integration and EV accommodation, we demonstrate the contribution of our approach to this problem of planning or scheduling. Obtained results quantifies the performance of the proposed method in terms of average energy difference based on number of EVs. The results can be used as a basis to decide the appropriate number of EV reservations.**

***Index Terms*—distribution systems, electric vehicle, Markov Chain, photovoltaic generation, vehicle-to-grid,**

I. Introduction

In traditional power systems, where distribution networks are more passive, forecasting methods could greatly and sufficiently support transmission system operation and planning, through predicting aggregated amount of consumption at the substation levels. Nowadays integration of many small-scale distributed energy resources to distribution systems (DS) makes these network more active [1], [2], [3]. Meanwhile exploiting clean energy with lower operational cost is attracting interest, hence most of new installation of distributed energy resources are renewable.

From capability of control and dispatching perspective, there are mainly two categories of renewables: Variable Renewable Energy (VRE), and controllable Renewable Energy. VRE is non-dispatchable energy source because of its fluctuating nature such as wind and solar power. In the contrary, controllable resources are dispatchable such as hydroelectricity and biomass which may be ramped up or down to match demand.

The main challenges of integrating renewable energy come from the variable type (wind and solar power) with its limited predictability characteristics. The variability in electrical power systems has been always an important issue in supply-demand balancing, but what makes it crucial nowadays is due to the variability on supply side rather than only on demand side, and the uncertainty of the available resources.

The VRE has some characteristics which give it the potential to impact power systems. The first property of a VRE is its variability which is derived from variations of the wind speed and levels of solar irradiation for power generation from wind and solar as the main VRE resources. In this regard, even if consumption behaviour of customers in the grid could be captured and forecasted with high accuracy, but prediction of aggregated amount of net consumption (i.e. the difference between total load and total distributed generations), in case of high VRE penetration is quite challenging [4], [5], [6].

Ignoring the impacts of VREs could bring even some emerging threats to the transmission systems (TS) which may make system operator decide to shed some loads to save the whole system from frequency or voltage collapse [7]. A general solution to this management challenge in transmission system is to get some contribution from distribution system operator (DSO) to mitigate the undesired impacts of VREs [8], [9]. DSO should ensure a scheduled or definite trajectory of power exchange at the primary substation level with its upstream transmission system. This objective can be achieved by either curtailing some loads or generators, or using flexible resources like storage units in the network [10], [11]. The former would result in higher cost, customer dissatisfaction, and environmental issues with respect to the latter choice, however the lather choice is efficient if there is adequate low cost flexibility in the system [12].

As lowering the cost of flexibility is important, installation of distributed bulk storage units may not be the best choice. Instead, getting contribution of available plug-in electric vehicles (EV) to system energy management could waive or reduce initial investment or installation costs.

There are a lot of discussions in literature about the impacts of EVs on system control and management as well their contribution as power reserve [13], [14], [15], [16], [17]. However, the main duty of these devices is transportation, and the way these EVs are involved in ancillary services or power balance is similar to demand response approaches.

In this paper, we describe a context in which EVs contribute to energy management in the same way the utility-owned stationary storage units are utilized; this means the contribution could be guaranteed, hence DSO can safely alleviate the out-of-schedule power demand or supply at the primary substation (i.e. coupling point of distribution and transmission networks).

In this context, we assume DSO makes contracts with some aggregators or car sharing companies who own and manage some parking lots (PL) in the network. The car sharing company may do some analysis to estimate some information like the number of available cars in each PL at each time-slot of the day, the state of the charge (SOC) of the batteries of the cars, number of reserved/booked cars by drivers, etc. Based on such information, it could offer some sort of power reserve to DSO.

In our paper, we address the scheduling challenge of such flexibility from DSO perspective. We provide a mathematical tool to DSO to estimate how many cars to book in advance for satisfying the scheduled profile of power exchange with transmission network. In case of power deficit or surplus with respect to the scheduled profile, DSO will use the batteries of the booked cars. Of course underestimation would result in imperfect demand correction, and overestimation would imply extra costs.

The methodology proposed in this paper is based on Markov Chain modelling. Charging and discharging of EVs are described as stochastic processes. State of EVs's charge is modelled based on discrete time Markov Chain. It follows a chain of linked events, in which what happens in the next state depends only on the current state of the system. Using this approach, a metric can be obtained to correlate the number of EVs to be reserved, and the average energy difference between the scheduled and real power exchange at the primary substation. This metric gives an insight to network planner or scheduler (e.g. DSO) to recover some level unscheduled power exchange between Ts and DS, by reserving a certain number of EVs in parking lots.

The rest of this paper contains the following discussions: the methodology of our proposed solution will be introduced in Section II. To demonstrate the performance of the new solution, we applied it to a realistic case of an urban distribution network accommodating several parking lots of EVs under high PV penetration scenario. The experiments and the results are briefly demonstrated in Section III. The paper will be concluded with some short remarks in Section IV.

II. Methodology

In this section, proposed methodology is discussed. The proposed model is based on developing a Discrete Time Markov Chain (DTMC) for capturing the proper number of required EVs for reserve. Firstly, Markov Chain modelling is described, then the discussed problem is formulated, and a metric is proposed to o correlate the number of EVs to be reserved and the average energy difference between the scheduled and real power exchange at the primary substation. This metric is defined to support determination of appropriate number of EVs to be booked, in cost-benefit analyses. Finally, the procedure of applying the proposed method is summarized.

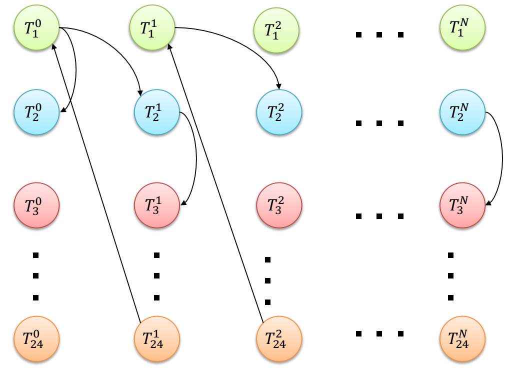

Fig. 1. Markov Chain model for EV units contribution to DSO.

A. Markov Chain

Markov models are statistical models in which we assume Markov property or memorylessness. Two main models in this area are Markov chain and Markov Random Field (MRF) that has been applied in various applications [18], [19]. The Markov chain model is a well known tool to analyze the behavior of the modeled system. The Markov chain model is based on states and transition probabilities [20]. This model satisfies Markov property in the sense that each state only depends on the previous state. Eq. (1) expresses this property in terms of conditional probabilities.

$$P(T_m|T_1, T_2, ..., T_{m-1}) = P(T_m|T_{m-1}) \tag{1}$$

In Fig. 1 Markov chain model for our discussed problem has been illustrated. T_m^n represents the state of available EVs used for providing flexibility at m^{th} time interval of the day (i.e. m hour after midnight), where n indicates the number of fully charged EVs. Transition probability matrix of the first time interval (i.e. from hour 00.00 to hour 01.00) is formed as follows:

$$TrPr\_1 = \begin{bmatrix} p_{0,0} & p_{0,1} & p_{0,2} & \cdots & p_{0,N} \\ p_{1,0} & p_{1,1} & p_{1,2} & \cdots & p_{1,N} \\ p_{2,0} & p_{2,1} & p_{2,2} & \cdots & p_{2,N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ p_{N,0} & p_{N,1} & p_{N,2} & \cdots & p_{N,N} \end{bmatrix} \tag{2}$$

where $p_{k,l}$ indicates the probability of availability of l fully charged units at time j if there were k fully charged units at time i. The overall transition probability matrix regarding

Fig. 1 would be as follows:

$$TransProb = \begin{bmatrix} TrPr\_1 & 0 & 0 & \dots & 0 \\ 0 & TrPr\_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & TrPr\_24 \end{bmatrix} \quad (3)$$

where $TrPr\_t$ is the transition probability matrix that is defined in Eq. (2) for $t = 1$. The size of this probability matrix is $24 * (N + 1) * 24 * (N + 1)$. The stationary distribution is formulated in the following equation.

$$\pi_l = [\pi_l^1, \pi_l^2, \dots, \pi_l^k, \dots, \pi_l^N]_{1 \times N} \quad (4)$$

where π_l^k is the probability of availability of k fully charged units when the state changes ($i \to j$).

B. Problem Formulation

The objective of DSO in operation is to minimize the energy difference between the real and the scheduled cases , while in scheduling phase or planning, the goal is to be able to cover this energy difference (i.e. ΔE). In the following equation, this energy difference has been normalized.

$$\Delta S = \frac{\Delta E}{E_u} \quad (5)$$

where E_u is the energy capacity of each unit. In this paper, he histograms of ΔS (see Fig. 5 for an example) are used to obtain transition probabilities of Eq. 2.

C. Average Energy Difference between Actual and Scheduled Demand

There are many criteria to evaluate the energy efficiency of power grids. These criteria can be categorized into economic, environmental, technical, feasibility and energy metrics [21]. Here a metric based on energy difference of actual and scheduled demand has been defined as follows:

$$|\Delta E_{avg}| = \sum_l \sum_k |\Delta E| \times \pi_l^k \quad (6)$$

where π_l^k is the probability of being in the specific state. This metric has been used as a metric to evaluate the performance of the proposed scheme.

D. Proposed Method

Having actual and scheduled demand as input data we can use the proposed model to investigate the performance of the method in terms of the energy difference metric. Algorithm 1 shows the pseudocode of the proposed method.

Algorithm 1 The proposed method algorithm

Data: Actual and scheduled demand

Result: Average energy difference metric

- Calculate ΔS using Eq. (5)
- Making histogram of ΔS
- Claculate transition propability matrix of Eq. (2)
- Calculate stationary probabilities of Eq. (4)
- Calculate average energy difference metric in Eq. (6)

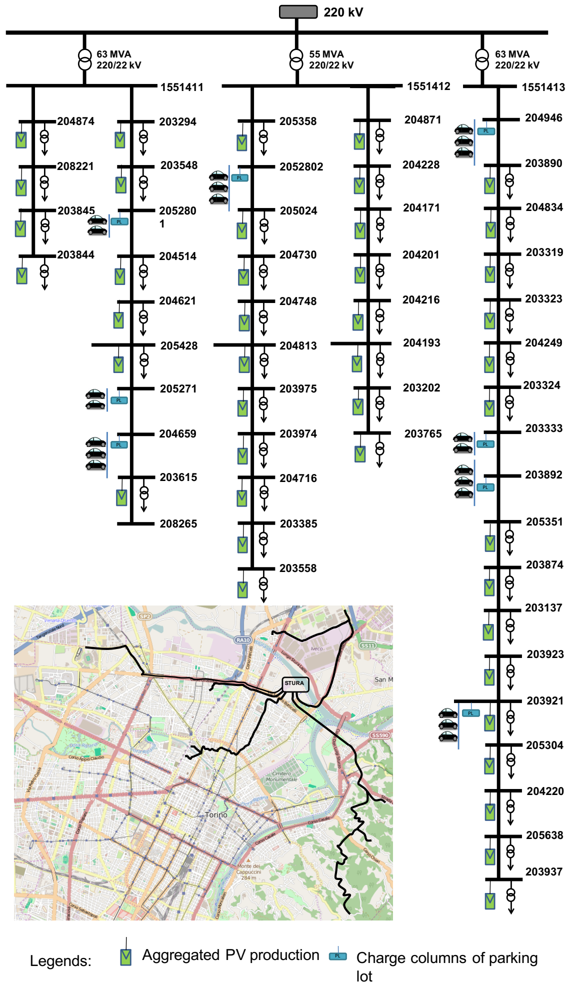

Fig. 2. Topology of case study grid with resources.

III. Experiments and Results

In this section used dataset is described in III-A, and will be followed by some results of study.

A. Dataset

The case study used for demonstration is a realistic network based on a portion of an urban distribution system in Northwest of Italy, city of Turin. The topology of this network is presented in Fig. 2. This is a medium voltage (MV) system with 3 transformers at the primary substation, 5 MV feeders, and 53 secondary substations. 43 substations supply low voltage grids with mainly residential loads. In order to stress the impact of VREs, we create a future scenario of smart grids where a high penetration of PV generation exists. In this scenario, most of the residential buildings in this urban area install roof-top PV panels [22]. There are 8 parking lots with charging columns directly supplied by the MV network.

The historic data used for PV production is generated as follow: the amount of produced energy by the PV panels were computed by the online NRELs PVWatts Calculator [23]. It allows choosing several parameters in order to give a

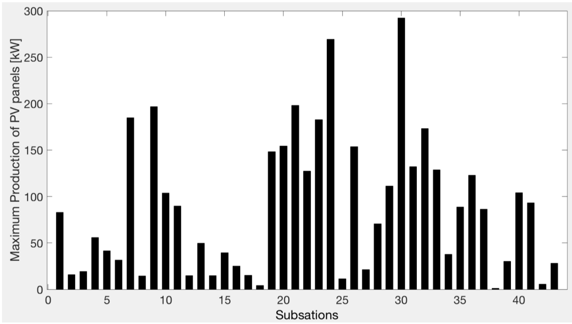

Fig. 3. Maximum power generation of PV panels under each substation [kW].

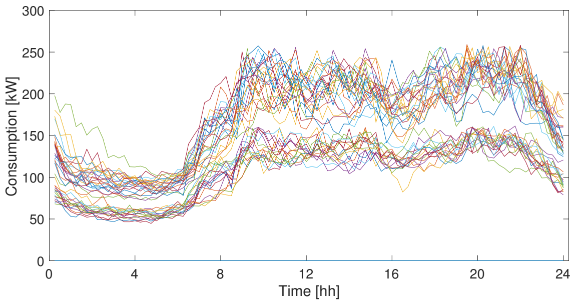

Fig. 4. Daily consumption of loads aggregated at 43 substations [kW].

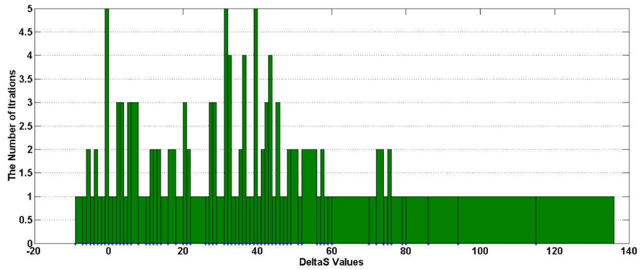

Fig. 5. Histogram of state transition from 17.00 to 18.00 - $\varDelta S$ [kWh].

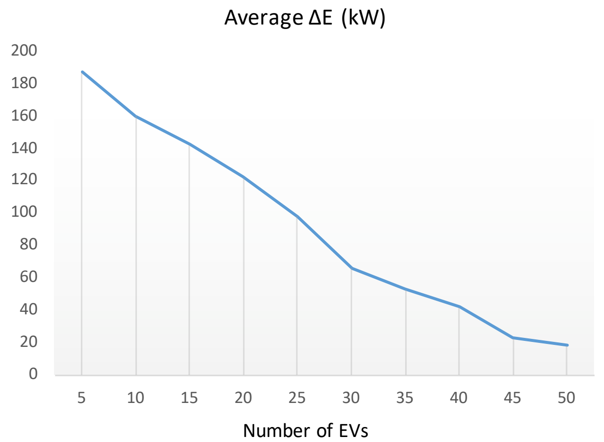

Fig. 6. Total energy difference versus total number of available fully charged EVs.

reasonable estimate of the energy production. For this test, the panel DC system size is set 1 kW with a standard module type, fixed array type, and DC to AC size ratio of 1.1 for the city of Turin. Hourly data of PV production for one year can be obtained for this panel size. Then, we made an assumption of different potential of PV production at 43 substations to scale up the calculated profile proportionally. Fig. 3 plots maximum production of PV panels under each secondary substations.

The loads in this network are mostly residential with a daily profile represented in Fig. 4 for all 43 substations.

Each parking lots (PLs) in our case study can serve up to 20 plug-in EVs by the charging columns. The EVs considered for the car sharing company of our scenario has battery capacity of 30 kWh. As described previously, the main objective of using EVs is green transportation. Each of these EVs can drive up to 150 km if they are fully charged. This is beyond distances normally needed for urban paths, therefore in our case study, when we address EVs for providing energy contribution (charge/discharge), they are assumed to have State-Of-Charge (SOC) in the range between 40% and 90%. This is to guarantee a minimum stored energy for the DSO or user, and also to limit the battery ageing effect.

B. Results

Following Algorithm 1, firstly to obtain the scheduled demand of the whole distribution system, we used a linear regression method to forecast the PV production of a typical day. Then, we use this data together with the residential load profiles presented in Fig. 4 to run a daily power flow from which we achieve the net demand of the system at the primary substation level.

The actual demand is the difference between the daily consumption and the calculated PV production from PVWatts.

Then, the $\varDelta S$ is calculated, and the corresponding histograms for all 24 transitions are obtained. Fig. 5 illustrates one example of such histograms for the state transition from hour 17.00 to 18.00.

The transition probability matrices are then formed to be used for calculating the stationary probabilities Eq. (4).

By considering different number of total booked EVs from 5 to 50, the average energy difference metric is calculated using Eq. 6.

The results plotted in Fig. 6 demonstrates that increasing number of booked EVs could reduce the difference between the average scheduled and actual energy at the primary substation. This trend seems logical, however the quantification offered by our proposed metric can be used in cost-benefit analysis tools to make decision to withstand some level of $\varDelta E$ for sake of EV reservation cost.

IV. Conclusion

Contribution of distribution systems to power system energy management is becoming crucial since more and more variable renewable energy resources are being integrated into the distribution networks. In this paper, we addressed the real time energy balance in distribution systems using available plug-in EVs as low cost flexible resources. In order to properly estimate the required capacity reserve and book EVs of some private car sharing companies, we proposed a metric which is based on Markov Chain approaches to quantitatively correlate the number of sufficient required cars with the amount of extra power demanded from upstream grid. The solution is applied to a realistic case, and the results provide a basis for decision makers to perform cost-benefit analysis and reserve appropriate number of EVs for reserve.

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